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Rigidity and Synchronization: Analyzing Online and Offline Price Dynamics[1]

Tim Ginker[*]   Alex Ilek[**]   Avichai Snir[***]

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[*] Bank of Israel, Information and Statistics Department. Email: ginker.tim@boi.org.il
[**] Bank of Israel, Research Department. Email: alexei.ilek@boi.org.il
[***] Department of Economics, Bar-Ilan University Ramat-Gan 5290002, Israel. Email: avichai.snir@gmail.com

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חטיבת המחקר, בנק ישראל ת"ד 780 ירושלים 91007
Research Department, Bank of Israel. POB 780, 91007 Jerusalem, Israel

Rigidity and Synchronization: Analyzing Online and Offline Price Dynamics

Tim Ginker Alex Ilek Avichai Snir

Abstract

We use panel data of regular prices posted by on- and offline stores. We study on- and offline price rigidity and price synchronization both within and across retailers. Our results suggest that, first, the physical cost of price adjustment has a small, albeit statistically significant effect on price rigidity. Second, prices are more similar within retailers than across retailers. Third, prices are more similar across online stores than across offline stores. However, price change synchronization is not higher across online stores than across offline stores. Fourth, our results suggest that the likelihood of pricing cascades is positively correlated with inflation. This underscores the importance of maintaining price stability in order to avoid coordination dynamics that may exacerbate the inflationary process.

קשיחות וסנכרון: ניתוח דינמיקת מחירים בחנויות מקוונות ופיזיות

טים גינקר, אלכס אילק ואביחי שניר

תקציר

אנו משתמשים בנתוני פאנל של מחירים רגילים המפורסמים על ידי חנויות מקוונות ופיזיות. אנו בוחנים את קשיחות המחירים ואת סנכרון המחירים הן בתוך והן בין הקמעונאים, במסחר מקוון ופיזי. התוצאות במחקר מצביעות על כך שראשית, לעלות הפיזית של התאמת מחירים יש השפעה חלשה, אם כי מובהקת סטטיסטית, על קשיחות המחירים. שנית, המחירים דומים יותר בתוך רשתות קמעונאיות מאשר בין רשתות קמעונאיות. שלישית, המחירים דומים יותר בין חנויות מקוונות מאשר בין חנויות פיזיות. עם זאת, סנכרון שינויי המחירים אינו גבוה יותר בין חנויות מקוונות מאשר בין חנויות פיזיות. רביעית, נמצא שמידת סנכרון המחירים בין הרשתות מתואמת עם שיעור האינפלציה הכללי במשק. ממצא זה מדגיש את החשיבות של שמירה על יציבות המחירים, מכיוון שסנכרון גבוה מעלה סיכון להיווצרות תהליך אינפלציוני שמזין את עצמו כתוצאה מתגובת שרשרת בה הפירמות מעלות מחירים כתגובה לעליית המחירים של מתחריהן.

1. Introduction

In models with sticky prices, nominal price rigidities play a key role in the amplification of macroeconomic shocks.[1] Economists, starting with Carlton (1986), Cecchetti (1986), Lach and Tsiddon (1992, 1996), Kashyap (1995), Levy et al. (1997), Blinder et al. (1998), and Slade (1998) have, therefore, studied the frequency and size of price changes, as well as the responsiveness of nominal prices to economic shocks.[2]

A leading explanation for price rigidity is the presence of menu costs (Anderson et al. 2015). These costs may be physical, such as the cost of reprinting price tags, or non-physical, such as the managerial effort required to process information, coordinate pricing decisions across different stores, and manage customers' reactions. Menu cost models predict that firms adjust prices infrequently, and that when they do, the price changes tend to be large.

This paper presents new empirical evidence on price rigidity and price synchronization using high-frequency panel data from the Israeli food retail sector. The data include both online and offline prices of identical products sold by the same retailers. We use it to compare the frequency, the size and the synchronization of price changes across online and offline stores.

Importantly, in online stores, the physical menu costs of adjusting prices are virtually zero. In addition, within a retailer, other costs of adjusting prices, such as managerial costs, are similar across online and offline stores. Consequently, we can utilize this data to examine the extent to which observed nominal price rigidity can be attributed specifically to physical menu costs, while keeping other costs fixed.

In addition to price rigidity, we study synchronization in price changes, a feature that plays a key role in recent models of monetary non-neutrality and inflation propagation (Carvalho, 2006; Konieczny and Rumler, 2006; Baley and Blanco, 2021). In particular, Nirei and Scheinkman (2024) propose that synchronization may amplify inflationary pressures via repricing cascades—mechanisms in which price changes by one firm triggers price changes by competitors, thus exacerbating the inflationary process.

1 For recent surveys, see: Klenow and Malin (2010), Leahy (2011), and Nakamura and Steinsson (2013).

2 See, for example, Dutta et al. (1999, 2002), Fisher and Konieczny (2000, 2006), Eden (2001, 2018), Chevalier et al. (2003), Bils and Klenow (2004), Dhyne et al. (2006), Knotek (2008, 2011), Nakamura and Steinsson (2008), Midrigan (2011), Kehoe and Midrigan (2015), Beradi et al. (2015), Anderson et al. (2015, 2017), Alvarez et al. (2016), Sudo et al. (2018), and Bonomo et al. (2022).

Our dataset has several advantages. Most importantly, it includes, for both the online and offline stores, the daily regular prices, as posted by the stores—rather than transactions or discounted prices. Therefore, we do not need to use sales filters to identify the regular prices, alleviating concerns about measurement errors (Nakamura and Steinsson, 2008; Eichenbaum et al., 2014; Kehoe and Midrigan, 2015). This is an advantage, as a substantial body of literature has shown that firms respond to shocks by adjusting their regular prices, which reflect fundamental prices. Temporary price changes ("sales"), on the other hand, play little to no part in the adjustment process (Nakamura and Steinsson, 2008, Alvarez et al., 2016, Anderson et al., 2017). Another advantage of the dataset is that is representative, as the retailers included in it have, in total, a market share of about 45%.[3]

To our knowledge, this is the first study to analyze panel data of regular prices of identical products sold simultaneously in online and offline stores belonging to the same retailers.[4] This is important, because the physical costs of adjusting prices online is virtually zero and, therefore, according to menu cost theory, prices should be more flexible online than offline. Moreover, the lower search and switching costs in online markets suggest that synchronization across online firms should be higher than across offline firms (Gorodnichenko and Talavera, 2017). Yet empirical evidence is mixed.

Gorodnichenko and Talavera (2017) and Gorodnichenko et al. (2018) find that online prices change more frequently than offline ones, but that synchronization across online firms is limited. In contrast, Cavallo and Rigobon (2016) and Cavallo (2018) report that online prices of retailers operating both online and offline channels, exhibit rigidities similar to those observed offline. Cavallo (2017) further shows that online and offline prices for a given retailer are often identical.

Our data allow us to extend the existing literature in three ways. First, the panel structure enables a direct comparison of price rigidity across online and offline formats of identical products sold by the same retailers. Second, we examine the synchronization of price changes both within and across retailers, comparing online and offline environments. Third, the sample period spans a significant shift in inflation: twelve-month inflation was

[3] Market share estimate based on BDI company rankings, available at https://www.bdicode.co.il/en/category/eng_commerce/eng_commerce_supermarket/, as observed in June 2024.

[4] Bonomo et al. (2022) have also used a dataset containing Israeli online and offline prices. They use it to study the within store price change synchronization.

below 1 percent during the first half of 2021 and rose to over 5 percent by 2022–2023. This variation provides a natural setting to assess how synchronization responds to changing inflationary conditions.

Our first set of findings corroborates earlier results. Within retailers, prices tend to be highly uniform across stores. The average daily share of identical prices ranges from 0.44 to 0.95, depending on the retailer, consistent with Cavallo (2017) and DellaVigna and Gentzkow (2019). Across retailers, however, price dispersion is substantial: the share of identical prices is 0.25–0.34 for online stores and 0.17–0.25 for offline stores. Thus, while intra-retailer pricing is largely uniform, inter-retailer dispersion is significant.

Synchronization of price changes across retailers is limited. Even at the monthly frequency, only 31 percent of online stores adjust prices in response to changes by a competitor, in line with estimates reported by Gorodnichenko and Talavera (2017). Notably, this is comparable to synchronization levels observed across offline stores, suggesting that lower search costs in online environments do not necessarily yield stronger coordination.

Our second set of findings is novel. We find that the interval between online price changes is only modestly shorter—by an average of 6.2%—than that of offline stores. In our sample, regular online prices change, on average, every 256 to 338 days, compared with 273 to 410 days for offline stores. Consistent with this finding, small price changes are slightly more common online than offline.

Taken together, these findings support menu cost theory: eliminating physical costs reduces the frequency of price changes. However, the effect is quantitatively limited. On average, removing physical costs shortens the time between price changes by only 6.2 percent.

We also find that synchronization within retailers occurs primarily at weekly or monthly intervals. The daily synchronization index from Gorodnichenko and Talavera (2017) ranges from 0.20 to 0.33 across retailers. This rises to 0.29–0.64 at the weekly level and 0.58–0.79 monthly, indicating that coordination operates over longer time horizons.

Finally, we document a positive relationship between inflation and synchronization, consistent with models of inflation cascades (Nirei and Scheinkman, 2024). When twelve-month inflation was around 3 percent, the synchronization index across retailers was approximately 0.10. As inflation rose above 5 percent, the index increased to over 0.20.

This suggests that firms are more likely to coordinate or follow competitors' pricing decisions in high-inflation environments.

The rest of the paper is organized as follows. In Section 2, we describe the data, in Section 3 we present the empirical analysis, and Section 4 concludes.

2. Data

Since May 20, 2015, all large food retailers operating in Israel are required by law to publish online the prices of all the products offered in each of their stores. If a retailer changes a price, the online database has to be updated within one hour. These data are scraped and stored by the Bank of Israel (*BoI*) IT Department on a daily basis.

Based on this dataset we use observations of the prices of products offered by retailers that satisfy the following criteria: (1) They have an online store, and (2) the BoI collected at least three years of data of their online store. There are three retailers that satisfy these conditions: Shufersal, Victory, and Global Retail.[5] According to BDI, the largest business information group in Israel, in 2023 these three retailers had a combined market share of about 45%.[6]

Unlike typical scraped data (e.g., Cavallo, 2018), where only the transaction ("shelf") prices are available, the BoI collects the regular prices, as posted by the stores (Bonomo et al., 2022). I.e., the BoI collected the regular price, as posted by the store, rather than the transaction prices (which can also include "sales").

Our sample includes daily price data for all products (excluding fruit and vegetables) offered by the online stores of the three retailers, as well as daily price information for all products available in the 10 largest offline stores of each retailer.

We define a store's size as the average number of products/day. Appendix A contains a map of the location of the offline stores. On average, an online (offline) store in our sample carries 11,110.7 (8,757.6) products, where a product is defined by its UPC. In the analysis below, when we compare prices across stores, we focus on the 1,903 products that are available in all stores. The data is available for January 1, 2021–December 31, 2023.

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5 Until 2023, Global Retail was known as "Yenot Bitan."

6 Source: https://www.bdicode.co.il/en/category/eng_commerce/eng_commerce_supermarket/, accessed September 22, 2024.

3. Empirical analysis

3.1 Frequency of price changes

Menu cost theory postulates that prices do not change continuously because price changes are costly (Alvarez et al., 2016). These costs may be physical, or not physical, such as managerial costs, pricing points, etc. (DellaVigna and Gentzkow, 2019, Knotek, 2024). If the main barrier to price changes is physical menu costs, then one would predict that online prices should change more often than offline prices, since the physical costs of changing online prices are negligible (Lee et al., 2009, Gorodnichenko and Talavera, 2017, Cavallo, 2018). However, if the main barriers to price changes are costs such as managerial costs (Zbaracki et al., 2004), or reputational costs (Rotemberg, 2005), then the frequency of price changes within a given retailer should be similar across online and offline stores.

To study the price rigidity at on- and offline stores, we calculate the duration between price changes for a product in a store as $-\left[\ln(1-\bar{f}_{i,s})\right]^{-1}$, where $\bar{f}_{i,s}$ is the average frequency of price changes of product i in store s (Nakamura and Steinsson, 2008). Table 1 reports the averages over all products.

On average, online stores change prices every 286.1 days, compared to 304.4 days in offline stores.[7] Comparing on- and offline stores, the difference in the average times between on- and offline stores is, therefore, 6.2%. There is, however, variation across retailers. For two retailers, online price rigidity is lower by 4.9%–6.4% than offline price rigidity. For the third retailer, the difference is 19.4%. Thus, although the average difference between the durations in on- and offline stores is not large, for one retailer, the difference is considerable.

In comparison, Gorodnichenko and Talavera (2017) use data of prices of retailers that operate only online stores and find that online prices last, on average, 3 weeks. They conclude that online prices are quite flexible. Cavallo (2018) that uses data of online prices of products offered by food retailers that offer both on- and offline stores, finds that regular online prices change every 7.6 months. He argues that this value is comparable to the price rigidity reported for offline stores.

[7] Comparing our results with Ribon and Sayag (2013), who use data collected for calculating the CPI, suggest that prices in Israel became more rigid over time. Ribon and Sayag (2013) report that over 1999–2011, prices changed, on average, every 6–9 months, with food prices changing every 8 months. We find that in 2021–2023, prices changed every 8.5–13.7 months.

Table 1. Average number of days between price changes

Retailer	Online	Offline	Difference	*t*-statistics
Shufersal	256.11	273.16	−6.4%	4.17***
Victory	337.87	410.11	−19.4%	17.78***
Global Retail	266.46	279.87	−4.9%	2.77***
Total	286.06	304.39	−6.2%	7.08***

Notes: The table gives the average number of days between price changes for online and offline stores, where the average number of days between price changes is calculated as $-\left[\ln(1-\bar{f}_{i,s})\right]^{-1}$, where $\bar{f}_{i,s}$ is the average frequency of price changes of product i in store s. The difference column gives the log difference between the online and offline columns. The *t*-statistics column gives the *t*-test statistics for comparing the distributions in the online and offline stores. *** - $p < 0.01$.

Our results, therefore, support Gorodnichenko and Talavera (2017) in suggesting that online prices change more often than offline prices. In line with Cavallo (2018), however, the rigidity of online prices is still significant. The average online price in our data changed every 8.5–11.3 months in a period with average inflation of 3.4%.

Our results, therefore, suggest that the physical costs of changing prices have only a modest effect on price rigidity. This result is particularly striking because the physical cost of changing a price in an Israeli offline store is significant, because Israel has an item pricing law.[8] The physical cost of changing a price of a product in an online store, on the other hand, is virtually zero (Gorodnichenko and Talavera 2017).

The result is striking also because during our sample period, several supermarket chains that operated online stores reduced their online activity, claiming that the profit margins in the online market are smaller than in the offline market. Yet, small profit margins should force retailers to conduct more price changes to keep their prices competitive. Therefore, we could expect that online prices would change more than offline prices even if on- and offline menu costs were the same. Thus, the 6.2% difference in the time between price changes of on- and offline prices is likely to be an upper bound on the effect of removing the physical menu costs.

To summarize, our results suggest that more than 90% of the duration between price changes must be explained by factors other than the physical costs of price adjustments, such as consumer antagonization (Rotemberg, 2005), implicit contracts (Levy and Young,

[8] In a country with item pricing laws, retailers must post a price tag on every item that is offered for sale. Bergen et al. (2008) find that such laws increase prices by about $0.20, suggesting that they have a significant effect on the cost of price adjustments.

2004), information costs (Reis, 2006), pricing points (Knotek, 2024), and managerial costs (Zbaracki et al., 2004, DellaVigna and Gentzkow, 2019). In addition, Strulov-Shlain's (2021) results suggest that Israeli retailers, like their US counterparts, might not be responding optimally to changes in market conditions.

3.2 Size of price changes

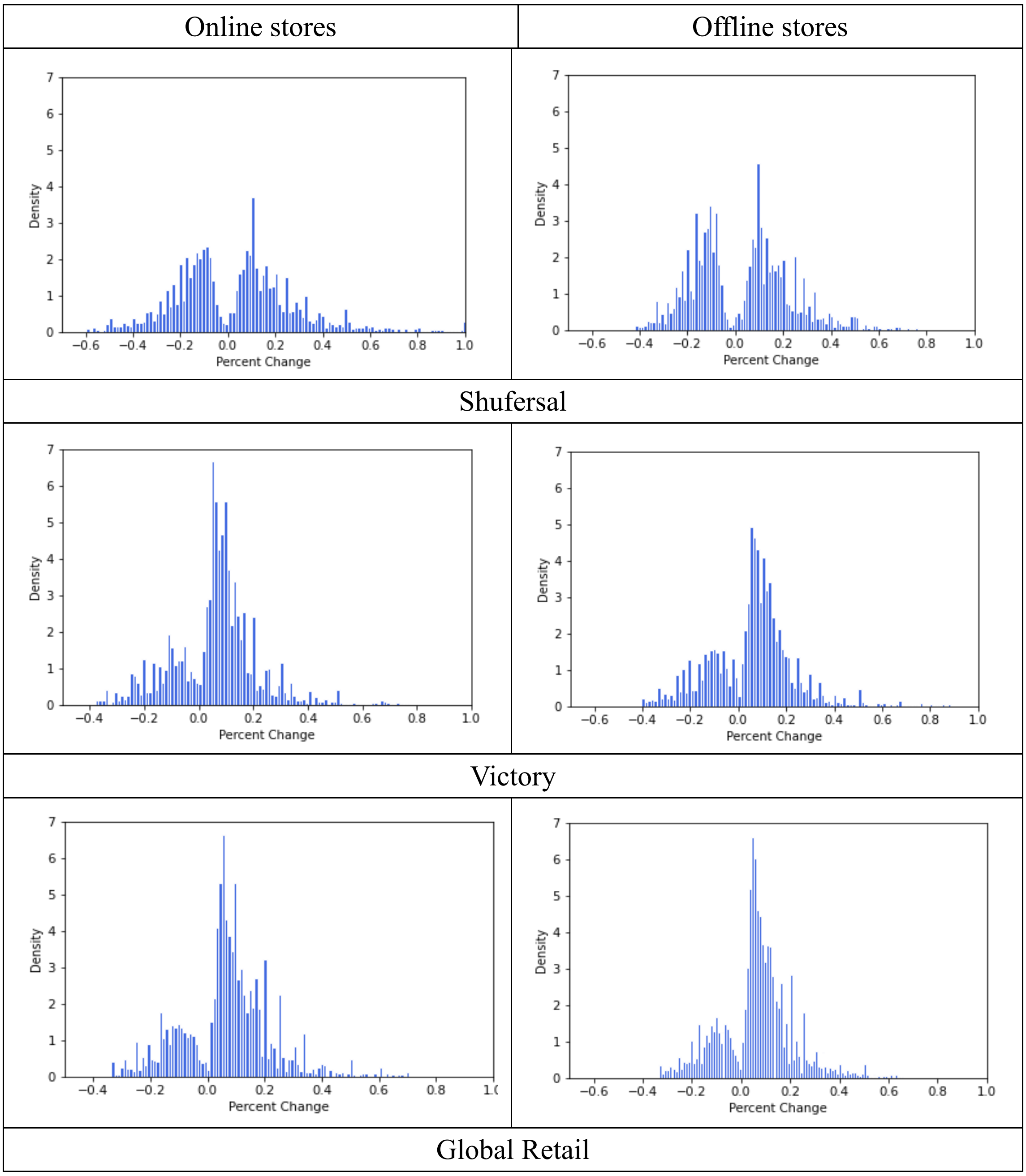
Menu cost theory predicts that retailers should avoid small price changes. However, in online stores, that have low physical costs of price adjustments, we should expect more small price changes than in offline stores. The results above, which suggest that online prices are only slightly more flexible than offline prices, imply, however, that the differences between the share of small price changes in on- and offline stores should be small.

Figure 1 depicts the distributions of price changes, calculated as log differences, by retailer. The left-hand (right-hand) side panel gives the distributions of price changes in online (offline) stores. Table 2 gives summary statistics of the distributions.[9]

Three things stand out. First, consistent with positive inflation in the sample period, the distribution is skewed to the right. Across the three stores, the average price change in online (offline) stores is 4.8% (3.8%), and the skewness is 1.1 (0.4). Second, there are very few small price changes. In both online and offline stores, the share of price changes smaller than 1% is, at most, around 1%. The share of price changes smaller than 5% is 5.7%–18.9%, depending on the retailer. These figures are consistent with Cavallo and Rigobon (2016), Cavallo (2018) and Giullietti et al. (2020), but are much smaller than reported by Midrigan (2011), and Beradi et al. (2015), among others. For comparison, Gorodnichenko and Talavera (2017) report that in their sample of US and Canadian online prices, 50% of the price changes are smaller than 3% and 4%, respectively.

[9] To calculate the kurtosis, we follow Alvarez et al. (2016) in using the normalized price changes.

Figure 1. Histograms of log price differences



Notes: The figure depicts the distributions of the size of log price differences. The left-hand (right-hand) side depicts the distributions of price changes in online (offline) stores.

Third, small price changes are more common in online stores than in offline stores. For two of the three retailers, the shares of small price changes (1%–5%) is consistently higher in online stores than in offline stores. This result is reversed only for Global Retail, which is the smallest of the three retailers. Thus, the results on the size of price increases complement those on the frequency of price changes. Small price changes are more common in on- than offline stores. However, the differences between the shares of small on- and offline changes are small.

Table 2. Descriptive statistics of the size of price changes

Retailer		Online	Offline	t/F-stat.
Shufersal	Mean	4.54%	2.82%	27.59***
	Standard Deviation	28.43%	20.36%	13842.87***
	Mean Abs. Change	21.59%	17.30%	119.27***
	Skewness	1.13	0.42	
	Kurtosis	5.90	2.91	
	Less than 1%	0.73%	0.72%	0.38
	Less than 2%	1.47%	1.30%	5.21***
	Less than 3%	2.38%	1.73%	17.05***
	Less than 4%	3.87%	2.70%	24.64***
	Less than 5%	5.71%	5.16%	26.84***
	KS (standardized)			0.10***
Global Retail	Mean	7.00%	6.33%	4.05***
	Standard Deviation	15.97%	14.93%	43.51***
	Mean Abs. Change	13.72%	12.78%	8.43***
	Skewness	0.355	0.217	
	Kurtosis	4.357	4.103	
	Less than 1%	0.81%	1.10%	2.51**
	Less than 2%	2.83%	3.41%	2.86***
	Less than 3%	5.96%	7.05%	3.84***
	Less than 4%	10.03%	12.49%	6.75***
	Less than 5%	16.64%	18.92%	5.27***
	KS (standardized)			0.03***
Victory	Mean	6.45%	6.13%	1.74*
	Standard Deviation	15.87%	18.10%	179.03***
	Mean Abs. Change	13.41%	14.80%	11.26***
	Skewness	0.334	0.515	
	Kurtosis	4.876	5.111	
	Less than 1%	1.14%	0.99%	1.45
	Less than 2%	3.14%	3.04%	0.58
	Less than 3%	6.40%	6.32%	0.29
	Less than 4%	9.76%	9.18%	1.97**
	Less than 5%	14.52%	13.06%	4.19***
	KS (standardized)			0.04***

Notes: The *t*/*F* column gives the test statistics for comparing the online and offline statistics for each retailer. We use *t*-statistics to compare the means, the means of the absolute price changes, and the share of the observations smaller than 1%–5%. We use the *F*-statistics to compare the standard deviations of the distributions. The KS row gives the Kolmogorov-Smirnov statistic for comparing the distribution of the sizes of online and offline standardized price changes. *- $p < 0.10$, ** - $p < 0.05$, ***- $p < 0.01$.

3.3 Price dispersion and synchronization of price changes

As Gorodnichenko and Talavera's (2017) note, it is easier for shoppers to switch between online than between offline stores. In addition, the cost of comparing prices online is lower than comparing prices offline. Gorodnichenko and Talavera's (2017), therefore, hypothesize that price dispersion across online stores should be low, while price change synchronization should be high. They find, however, that there is considerable price dispersion across online stores, and that price synchronization across online stores is quite limited. We can extend their findings by comparing the price dispersion and synchronization between on- and offline stores, both within and across retailers.

We start by looking at price dispersion. Panel A of Table 3 gives the results of an index used by DellaVigna and Gentzkow (2019) to measure the daily price dispersion in our sample. The DellaVigna and Gentzkow (2019) index is defined as the share of products (identified by their UPCs) for which the log-difference in prices is less than 1% in absolute value. The values in Table 3 can, therefore, be interpreted as the average shares of equal prices.[10]

To allow comparisons of the results across online and offline stores, we calculated the share of equal prices for each pair of stores, and then took the average over all the relevant pairs. The left-hand (right-hand) side of Panel A gives the results when we compare across (within) retailers.

We have three main findings: First, consistent with DellaVigna and Gentzkow's (2019), we find that daily prices are more similar across stores belonging to the same retailers than across stores belonging to different retailers. The within retailer shares of identical prices are 0.95, 0.57, and 0.44 for Shufersal, Victory and Global Retail, respectively. Thus, the dispersion of the index is similar to what is reported by DellaVigna and Gentzkow's (2019) for the US. The indices across retailers are: 0.34, 0.25 and 0.26 if we compare across online stores, and 0.25, 0.21 and 0.17 if we compare across offline stores. It therefore seems that Israeli retailers, like their US counterparts, tend to lean towards uniform price policies, but there is considerable price dispersion across retailers.

[10] DellaVigan and Gentzkow (2019) consider prices that deviate by as much as 1% as equal because they use scanner data and, therefore, prices in their sample are measured with noise. Our observations are on prices that are reported by the retailers. Thus, in our data, the DellaVigna and Gentzkow (2019) measure is equivalent to measuring the share of equal prices.

Second, prices are more similar across online stores belonging to different retailers than across their corresponding offline stores. The share of identical prices across online stores ranges from 0.25 to 0.34 (averaging 0.29), compared with 0.17 to 0.25 (averaging 0.22) across offline stores. Therefore, the share of equal prices across online stores is only slightly higher than across offline stores.

Third, price dispersion across online stores is still considerable. Given the low costs of switching between online stores, it is noteworthy that 66%–75% of the prices are different across stores. This result is consistent with Gorodnichenko and Talavera's (2017), and it suggests that low search costs and low costs of switching between stores might not be enough to eliminate price dispersion.[11]

Table 3: Indices of price dispersion and synchronization

A. DellaVigna and Getnzkow (2019) measure of equal daily prices

	Across retailers		Within retailers	
	Online	**Offline**	**Retailer**	
Shufersal–Victory	0.34	0.25	**Shufersal**	0.95
Shufersal–Global Retail	0.25	0.21	**Victory**	0.57
Victory–Global Retail	0.26	0.17	**Global Retail**	0.44
Total	0.29	0.22	**Total**	0.83

B. Gorodnichenko and Talavera's (2017) measure of price change synchronization

	Across retailers		Within retailers		
Frequency	**Online**	**Offline**	**Shufersal**	**Victory**	**Global Retail**
Daily	0.07	0.10	0.33	0.22	0.07
Benchmark	0.00	0.00	0.10	0.10	0.10
Weekly	0.19	0.21	0.64	0.48	0.29
Benchmark	0.03	0.03	0.15	0.12	0.13
Monthly	0.31	0.36	0.77	0.58	0.48
Benchmark	0.09	0.10	0.27	0.15	0.18

Notes: Panel A. gives the DellaVigna and Getnzkow (2019) index of price similarity across stores. The index is calculated for each pair of stores, and then averaged over all relevant stores. The left-hand side panel gives the results across retailers. The right-hand side panel gives the results within retailers. The Total represents the turnover-weighted average. Panel B gives the Gorodnichenko and Talavera's index of price change synchronization. The index is calculated at daily, weekly, and monthly frequencies. The benchmark rows give benchmark values, which are the expected indices under no coordination. The left-hand side panel gives the results across retailers. The right-hand side panel gives the results within retailers.

[11] In Israel, the cost of comparing prices across offline retailers is also low. As described in the data section, since 2015 all major food retailers post the prices of all the goods that they offer online. This data is collected and made available to shoppers via specialized applications that can be downloaded for free. Ater and Rigbi (2023) show that since this price information was made available, price dispersion across stores decreased. Consistent with our findings, they report that most of the decline in price dispersion was within retailers.

To look at the synchronization of price changes, we employ the Gorodnichenko and Talavera's (2017) index of synchronization.[12] It is calculated as the average share of stores that adjust the price of a product, in response to a change in the price of an identical product in another store.

The left-hand side of panel B of Table 3 gives the results across retailers, and the right-hand side gives the results within retailers. All the indices are calculated at daily, weekly, and monthly frequencies.

Gorodnichenko and Talavera's (2017) index of synchronization is convenient because it can be interpreted as a measure of responsiveness. However, the synchronization index is sensitive to the number of stores included in its calculation, which complicates direct comparisons between online and offline formats, given that our sample includes more offline than online stores. Moreover, the index captures not only responses to competitors' price changes but also common reactions to aggregate economic shocks. To address these concerns, we report benchmark values—expected index values under the null hypothesis of no coordination (i.e., statistical independence) across stores—which serve as a reference for interpreting observed synchronization levels. We calculate the benchmark as follows. We use the fact that Gorodnichenko and Talavera's (2017) index represents a scaled sum of binary variables indicating the price change of good i at time t in store s. Thus, under the null hypothesis of no coordination, the expectation of the index is completely characterized by the probability of a price change for each good in each store. The algorithm is available online.[13]

We find, first, that when we compare across retailers, the level of price change synchronization is quite low, although it is much higher than predicted under no coordination. The indices are 0.07–0.10, 0.19–0.21, and 0.31–0.36 at daily, weekly and monthly frequencies. The weekly frequencies that we report are similar to those reported by Gorodnichenko and Talavera (2017) for online stores in the US and Canada. It therefore seems that even at a monthly frequency, only about 1/3 of the stores change the price of a product when a competitor changes the price of an identical product.

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[12] For a given good i, time t, and store s, the index is defined as follows: $Synchrinization_{i,s,t} = \frac{\sum_S 1\{P_{i,t,s} - P_{i,t-1,s} \neq 0\} - 1}{\sum_S 1\{P_{i,t,s} \neq missing \cap P_{i,t-1,s} \neq missing\} - 1}$.See Gorodnichenko and Talavera (2017), p.264.

[13] github.com/timginker/Computing-benchmark-for-Gorodnichenko-and-Talavera-s-2017-index-of-price-synchronization..git.

Second, our results suggest that there are almost no differences between the synchronization of price changes across on- and offline stores. The small differences that we find are mostly explained by the larger number of offline stores, leading to a slightly higher benchmark values for offline stores than for online stores. We do not find evidence, therefore, that the greater facility with which shoppers can switch between on- than offline stores affects price change synchronization across stores belonging to different retailers.

Third, looking within retailers, we find that price changes are strongly synchronized across stores, but only if we look at weekly and monthly frequencies. Within a retailer, the shares of stores that change the price of a product in response to a change in the price of an identical product at another store are 0.07–0.33, 0.29–0.64 and 0.48–0.77 at daily, weekly, and monthly frequencies, respectively. Thus, within stores belonging to the same retailer, the price change synchronization at daily (weekly) frequency is 14.6%–42.9% (60.4%–83.1%) of the synchronization at the monthly frequency.

Using a different dataset of Israeli food retailers, Bonomo et al. (2022) show that a large share of price changes occurs on "peak days." Our results suggest that even within retailers, the timing of peak days varies across stores, perhaps because of idiosyncratic differences in price adjustment costs.[14] When studying the synchronization of price changes, it might be better, therefore, to focus on weekly or monthly data than on daily data.

3.4 Price change synchronization over the inflationary cycle

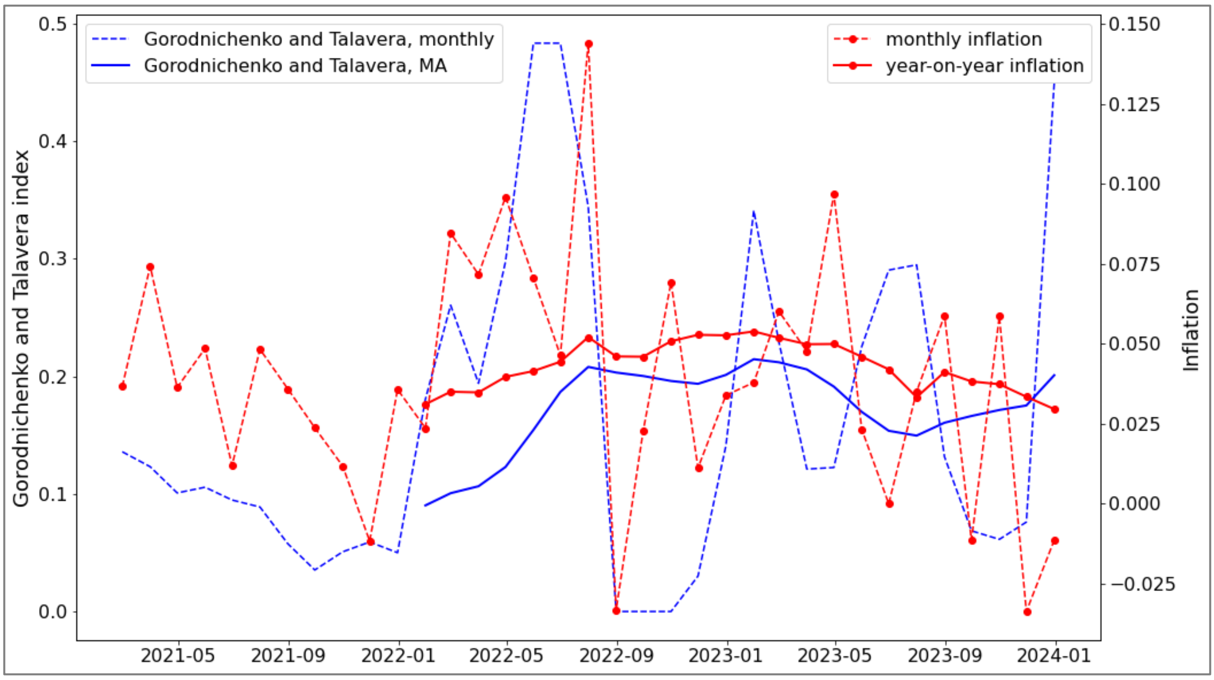
Nirei and Scheinkman (2024) argue that when inflation increases, retailers have a greater incentive to respond to price changes of competing firms. As a result, when inflation increases and one firm changes a price, some competitors are likely to follow, inducing more firms to change prices, thus leading to repricing avalanches. Their model, therefore, predicts that the synchronization between price changes should be correlated with the inflation rate.

To test this, we calculate for each week in the data the Gorodnichenko and Talavera (2017) index of price synchronization. We then derive the average monthly values. Figure 2

[14] For example, assume that there are two stores belonging to the same retailer. In store A, the busiest days are Mondays, Tuesdays and Fridays. In store B, the busiest days are Wednesdays, Thursdays and Fridays. As argued by Levy et al. (2010), stores might want to avoid changing a large number of prices when demand is high, so store A might prefer to change prices on Wednesdays and Thursdays, while store B on Mondays and Tuesdays.

depicts the resulting values of the index (blue dashed line), together with annualized monthly inflation (red dashed line). We find that the correlation between the two series is 0.31. The correlation is statistically significant at 10%.

Figure 2 - The average of the Gorodnichenko and Talavera (2017) index of price synchronization and inflation in Israel, 2021-2023.



However, the monthly data is affected by seasonality in both inflation and the Gorodnichenko and Talavera (2017) index, making it difficult to distinguish between trends in the correlation and temporary fluctuations.[15] We, therefore, also include in Figure 2 the 12-month moving average of the Gorodnichenko and Talavera (2017) index (solid blue line) and the 12-months inflation (solid red line). The correlation between the smoothed series is 0.70, and it is statistically significant at 1%. It therefore seems that the increase in the correlation between inflation and the synchronization of price changes is not driven by temporary or seasonal factors. We conclude that our results seem to support the mechanism suggested by Nirei and Scheinkman (2024). As inflation gets higher, retailers are more likely to respond to a price change by a competitor. In our data, in early

[15] One possible reason for seasonality in the Gorodnichenko and Talavera (2017) index is "pricing seasons" (Zbaracki et al., 2004). If producers negotiate new contracts with many retailers simultaneously, we are likely to observe that a number of retailers change prices at about the same time, leading to seasonal increases in the Gorodnichenko and Talavera (2017) index. Nakmaura and Steinsson (2008) also suggest the existence of pricing seasons, as they find that a large share of price changes take place in January, April, July and October.

2022, when 12-months inflation was around 3%, the Gorodnichenko and Talavera (2017) index was around 0.1. In early 2023, when the 12-months inflation was around 5%, the value of the Gorodnichenko and Talavera (2017) index more than doubled to 0.22. This finding underscores the importance of maintaining price stability in order to avoid coordination dynamics that may exacerbate the inflationary process.

4. Conclusions

Menu costs theory predicts that price changes should occur infrequently, and that small price changes should be rare. It also predicts that because online stores have low physical costs of changing prices, they should change prices more often, and have smaller price changes than offline stores.

Using a unique database that includes observations of prices of products offered in both on- and offline stores belonging to the same retailers, we find evidence consistent with both predictions. Online stores change prices more often, and small price changes are more common in on- than offline stores. However, we also find that the differences between on- and offline price rigidity are small. On average, prices in online stores last only 6.2% fewer days than in offline stores, and the likelihood of small price changes in online stores is only slightly higher than in offline stores. Our results therefore suggest that physical menu costs are likely to be only a small part of the total costs of price adjustments.

We also find that the likelihood of observing identical prices is higher across online stores than across offline stores belonging to different retailers. This finding is consistent with the low costs associated with searching and switching between online stores. This being said, the synchronization of price changes across online stores belonging to different retailers is not higher than the synchronization across corresponding offline stores. In addition, although price dispersion across online stores is lower than across offline stores, it is still high. On average, only 29% of prices are equal across online stores.

Finally, we find that consistent with models that predict that price change synchronization should be correlated with inflation, we find that the likelihood of observing a change in a price conditional on a competitor changing the price of an identical product is positively correlated with the inflation rate. Our results therefore suggest that when inflation increases, repricing cascades might become more common, exacerbating the inflationary process.

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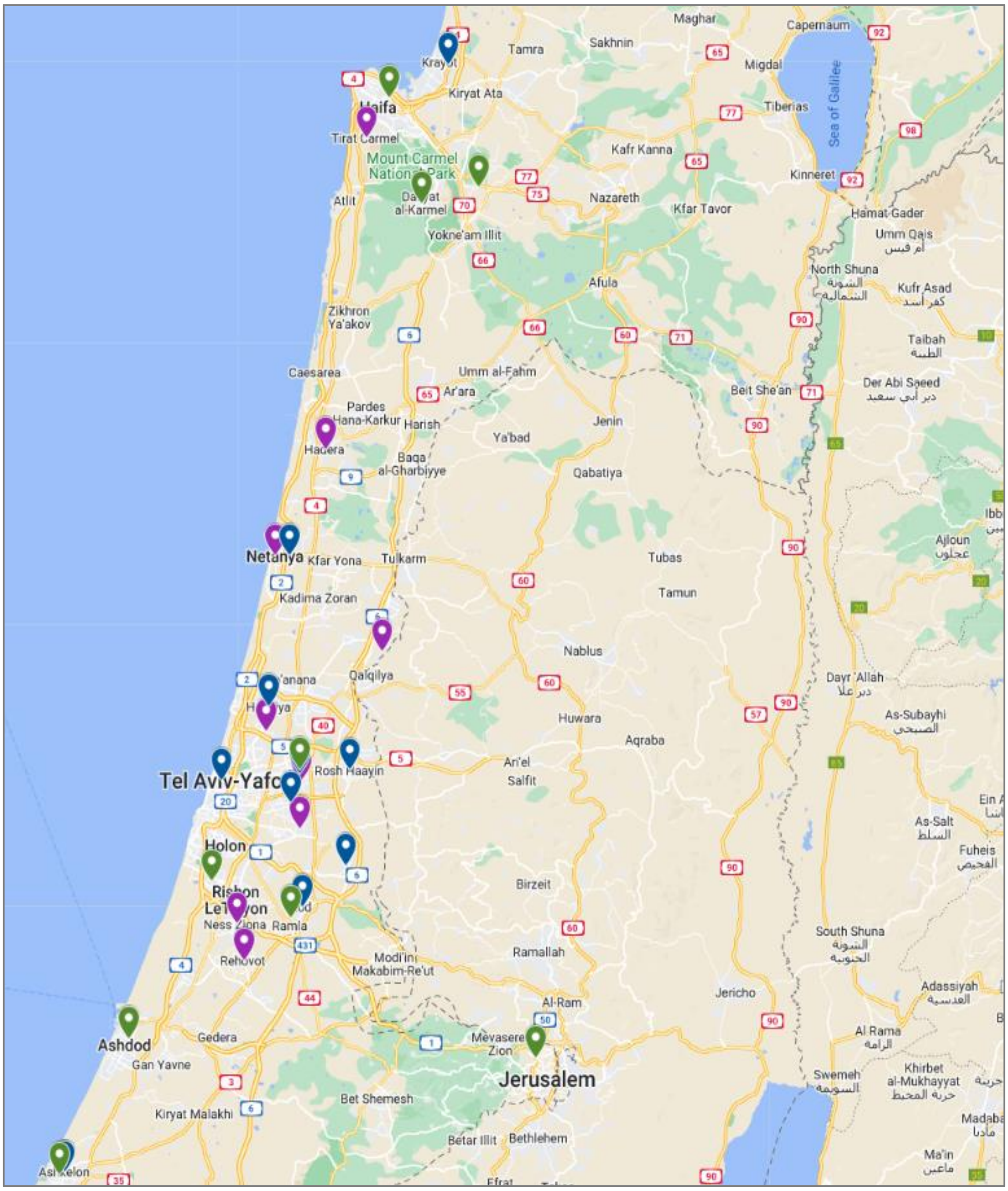
Appendix A

Table A1: A map of the location of the offline stores



Notes: The purple markers depict the locations of Shufersal's stores. The blue markers depict the locations of Victory's stores. The green markers depict the locations of Global Retail's stores. The map can be accessed at: https://www.google.com/maps/d/edit?mid=1pVQyI5bZ9kxkYk5i2jVmj1XuxiLkU7Q&usp=sharing